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CERTIFICATE

This certificate is issued in support of an application for Patent registration in a country outside New Zealand pursuant to the Patents Act 1953 and the Regulations thereunder.

I hereby certify that annexed is a true copy of the Provisional Specification as filed on 13 July 1999 with an application for Letters Patent number 336743 made by COMPUDIGM INTERNATIONAL LIMITED.

Dated 24 July 2000.

Neville Harris
Commissioner of Patents

COMMISSIONER OF PATENTS, TRADE MARKS & DESIGNS
NEW ZEALAND

336743

Patents Form No. 4

PATENTS ACT 1953

PROVISIONAL SPECIFICATION

INTERACTION PREDICTION SYSTEM AND METHOD

We, **COMPUDIGM INTERNATIONAL LIMITED, of Level 12, BOC House, 133-137 The Terrace, Wellington, New Zealand,** do hereby declare this invention to be described in the following statement:

INTERACTION PREDICTION SYSTEM AND METHOD

FIELD OF INVENTION

The invention relates to an interaction prediction system and method, particularly but not solely designed for predicting future revenue from individual gaming machines in a casino.

BACKGROUND TO INVENTION

Merchants today generate and collect large volumes of data during the course of their business. To compete effectively it is necessary for a merchant to be able to identify and use information hidden in the collected data, for example trends and patterns. On these trends and patterns the merchant may attempt to predict future revenue. The ask of identifying this hidden information has proved very difficult.

Traditionally the identification of trends or patterns has been achieved by running a query on a set of data stored in a database for example. The merchant first creates a hypothesis, converts this hypothesis to a query, runs the query on the database, and interprets the results obtained with respect to the original hypothesis.

One disadvantage of this verification driven hypothesis approach is that the merchant must form the desired hypotheses in advance. This is merely confirming what the merchant already suspects and does not provide the merchant with information which may be unexpected. In some circumstances the factors which must be taken into account, and the relevance of these factors with regard to other factors, cannot be anticipated by the merchant.

SUMMARY OF INVENTION

In broad terms the invention comprises an interaction prediction system comprising a memory in which is maintained an interaction database of interaction data representing interactions between customers and merchants; retrieval means arranged to retrieve from the interaction database data representing interactions between customers and merchants; a computer implemented neural network trained on data from the retrieval means and arranged to predict future interactions between

customers and merchants and to generate prediction data representing the future interactions between customers and merchants; and display means arranged to display to a user a representation of the prediction data.

Preferably one or more of the merchants operates from one or more commercial premises or stores.

Preferably the interaction data includes date and/or time data.

Preferably one or more of the interactions has a monetary value, and the interaction data obtained from the interactions includes the monetary value.

Preferably one or more of the interactions relates to the revenue generated from a gaming machine, and the interaction data obtained from the interactions includes a gaming machine identifier.

Preferably the neural network comprises a multilayer perceptron having ten hidden nodes, one output node and one or more input nodes, each input node arranged to receive interaction data involving a specific gaming machine.

In broad terms in another form the invention comprises a method of predicting interactions comprising the steps of maintaining in a memory an interaction database of interaction data representing interactions between customers and merchants; retrieving from the interaction database data representing interactions between customers and merchants; predicting future interactions between customers and merchants and generating prediction data representing the future interactions between customers and merchants with a computer implemented neural network trained on data from the retrieval means; and displaying to a user a representation of the prediction data.

In broad terms in another form the invention comprises a method of training a computer implemented neural network to predict interactions comprising the steps of maintaining in a memory an interaction database of interaction data representing interactions between customers and merchants; retrieving from the interaction database data representing interactions between customers and merchants; feeding the data to a computer implemented neural network; retrieving prediction data from

the neural network representing the future interactions between customers and merchants; retrieving actual data from the interaction database; and comparing the prediction data with the actual data.

Preferably the method further comprises the step of transforming the data retrieved from the interaction database before feeding the data to the neural network.

Preferably the steps of retrieving data from the interaction database, feeding the data to the neural network, retrieving the prediction data from the neural network, and retrieving the actual data from the interaction database are repeated until a good fit is obtained.

BRIEF DESCRIPTION OF THE FIGURES

Preferred forms of the interaction prediction system and method will now be described with reference to the accompanying Figures in which:

Figure 1 is a schematic view of the preferred system;

Figure 2 shows the interaction data used by the preferred system of Figure 1;

Figure 3 illustrates one possible source of interaction data;

Figure 4 is a schematic representation of a neural network;

Figure 5 shows one method of training the neural network;

Figure 6 shows the results of training the neural network of Figure 4 with the data from Figure 3;

Figure 7 illustrates use of the trained neural network ;

Figure 8 shows the interactions predicted by the network of Figure 4 once trained;

Figure 9 illustrates another possible source of interaction data;

Figure 10 is a schematic representation of another neural network;

Figure 11 shows the results of training the neural network of Figure 10 with the data from Figure 9; and

Figure 12 shows the interactions predicted by the network of Figure 10 once trained.

DETAILED DESCRIPTION OF PREFERRED FORMS

Referring to Figure 1, the preferred system 2 comprises a data processor 4 interfaced to a memory 6, the processor 4 and the memory 6 operating under the control of appropriate operating and application software. Stored in the memory 6 is a database of interaction data 8 representing interactions between customers and merchants as will be more particularly described below.

The processor 4 is connected to an input device 10, for example, a keyboard and mouse, and a display device 12, for example, a monitor. The processor 4 may also be connected to a suitable input/output device such as a disk drive 14 and may also be connected to a printer 16.

Data obtained through the input device 10, from memory 6 and from disk drive 14, is displayed to the user on display device 12 or output to printer 16. The processor 4, memory 6, input device 10, display device 12, disk drive 14 and/or printer 16 may be set up as a standalone computer or may be connected to further components in a network. Networks may be of any type, for example, internet, intranet, local area and wide area networks.

It is envisaged that the system 2 could include more than one processor to support distributed processing as will be more particularly described below.

Typically, a merchant will operate in a commercial premises or store from which a customer will purchase goods or services. The merchant may, for example, operate a casino or other gaming facility in which a number of gaming machines and stations are positioned at a common venue. Alternatively, the merchant may operate a petrol station or other retail outlet, the merchant may operate a warehouse facility or may offer a range of financial services.

The merchant does not necessarily need to operate from a commercial premises or store. For example, the merchant may operate from strategically-placed machines, for example, vending machines, parking meters, laundry machines, transportation ticketing machines and/or amusement machines. The merchant may also operate by mail, for example, a mail order catalogue service, direct market goods or services, or network market through a hierarchy of distributors and resellers. The merchant may alternatively operate from a website or other electronic medium. It will be appreciated that the nature of business of the merchant includes a wide range of activities.

The customer may be a purchaser of goods or services from the merchant. Where the merchant operates a casino or other gaming facility, the customer will be a patron depositing money in a gaming machine.

Referring to Figure 2, as the customer 20 interacts with the merchant 18, the interaction generates interaction data 8 which is collected as indicated at 22 and stored in memory 6. A typical record of collected interaction data is shown at 26. The record may include, for example, a merchant identifier where the interaction data includes interactions involving more than one merchant. The merchant identifier could be used to identify a particular merchant, and where a merchant operates from more than one geographic location, the merchant identifier, or some other identifier included in record 26, may identify the geographic location in which the interaction occurs.

The record 26 could also include a customer identifier. The merchant may, for example, issue an incentive supporter customer loyalty card which is then used by the customer during interactions with the merchant. The loyalty card preferably has stored on it a customer identifier. Alternatively, if the customer pays for the interaction using a credit card, eftpos or stored value card, the customer identifier could include an identifier obtained from the card.

Where the merchant operates a casino or gaming facility, the merchant may have assigned to each individual gaming machine a machine identifier. The merchant may also assign a machine bank identifier to each bank of gaming machines together with a suitable machine identifier to identity which machine in the machine bank was involved in the interaction.

The record 26 may also include data such as the date and/or time at which the interaction between the customer and the merchant took place and/or the cash value of the interaction.

The interaction data 8 is migrated to the memory 6 as indicated at 28. Migration may be performed, for example, by way of daily updates. It is advantageous to cleanse, catalogue and validate the interaction data 8 during migration of the data to the memory 6, and this could be performed by either the merchant or by a third party.

The memory 6 could be maintained by a merchant or alternatively, could be maintained by a third party. Updates to the memory could be carried out by the merchant directly, or alternatively the merchant could provide batched data to a third party for updating the data. Alternatively, a third party could be entrusted with the task of collecting and migrating the interaction data to the memory 6.

Figure 3 illustrates one possible source of interaction data, in which the merchant operates a casino or gaming facility. The merchant arranges a number of individual gaming machines into banks, for example, bank 30 and neighbouring banks 32, 34, 36 and 38. As a customer uses a gaming machine in a particular bank, the date, time, machine bank id and the value of the transaction is collected and stored in memory 6. The merchant may wish to estimate the revenue which will be generated by bank 30. The invention provides a system and method for making such a prediction.

Referring to Figure 4, in one preferred form of the invention, a neural network 50 is arranged to run on the processor 4. The preferred neural network could be implemented in C++, Visual Basic, or another object-oriented language suitable for the purpose. Where the system includes only one processor, each neuron could be arranged to run on that processor. Where the system includes more than one processor, the neurons could be arranged to run on different processors. Ideally each neuron will run on a separate processor.

The preferred neural network 50 is a multi layer perceptron having an input layer 52, a hidden layer 54, and an output layer 56. It is envisaged that the network 50 could include more than one hidden layer. Where the neural network 50 is arranged to process the data from Figure 3, the input layer 52 is provided with five input nodes,

each input node arranged to receive interaction data involving one of machine banks 30, 32, 34, 36 and 38.

Signals are received by nodes in the input layer 52. These signals are transformed and output to nodes in the hidden layer 54. As shown in Figure 4, the neural network 50 may be arranged so that output signals from each node in the input layer 52 are sent to each node in the hidden layer 54.

The output signal from each node in the input layer 52 may be multiplied by a weight before reaching a node in the hidden layer 54. In Figure 4, for example, signals having positive weights are shown in green, while signals having negative weights are shown in red. The absolute value of the weight may also be varied, and in Figure 4 the thickness of the line indicating a signal is proportional to the absolute value of the weight on that signal.

As shown in Figure 4, the preferred number of nodes in the hidden layer is ten, although it is envisaged that this number may be varied to a number suitable for the application to which the invention is directed.

Signals received by nodes in the hidden layer 54 are transformed and output to a single node in the output layer 56. Each node in the hidden layer 54 may be arranged to send an output signal to the single node in the output layer 56.

Once again, the signals may be weighted, and positive weights are indicated in green and negative weights are indicated in red. The absolute value of the weight may also be varied, and the thickness of the line is proportional to the absolute value of the weight attached to a particular signal.

The preferred neural network is arranged so that each node receives a signal as input, performs a transfer or activation function on the signal, and outputs a numerical value as a result of this function. This transfer function may be, for example, the following logistic function:

$$out = f(in) = \frac{1}{1 + \exp^{-in}}$$

Advantages of this logistic function are that it is infinitely differentiable, it is smooth, monotonically increasing, and maps the real line on the (0,1) interval. If the original signal is too strong, it will give an output close to 1. If the signal is too weak, it will give an output close to 0.

It is envisaged that other known functions suitable for the purpose could replace the above logistic function, for example a linear function such as:

$$out = f(in) = \frac{1}{L(in)}$$

where L is a linear function.

Although the preferred neural network is arranged so that nodes in the input layer 52 send output signals to the nodes in the hidden layer 54, and nodes in the hidden layer 54 send output signals to node(s) in the output layer 56, it is envisaged that some nodes in the input layer 52 may be arranged to transfer signals directly to node(s) in the output layer 56. Such direct connections may be suitable for approximating linear functions.

The preferred neural network is trained on interaction data retrieved from memory 6. Figure 5 illustrates one preferred method of training the neural network. The network is first initialised by setting initial signal weights as indicated at 70. One method of initialisation involves setting weights to random values initially.

As indicated at 72, data representing interactions between customers and merchants is retrieved from memory 6. Where the training method of Figure 5 is applied to the data from Figure 3, the interaction data will involve revenue from each of machine banks 30, 32, 34, 36 and 38. The data could represent, for example, revenue generated by each of the machine banks over a two week period.

As shown at 74, the data retrieved from memory 6 may be transformed in a manner suitable for the neural network. The range of values could be transformed, for example, so that the values belong in the (0,1) interval. The data could be scaled by a preprocessing function so that the maximum revenue of the machine bank during the two week period would be scaled to 1, and values less than the maximum lie between 0 and 1.

The preprocessing function could include a linear function, a non-linear function, or another neural network, to transform the values to a range suitable for the purpose.

As shown in 76, the data is then fed to the neural network. It will be appreciated that this data could be raw data retrieved from the memory at step 72, or could be data preprocessed by the step of 74.

The neural network then acts on the input data and produces an output value. This output value could be in the (0,1) interval where the input data has been preprocessed. Postprocessing may then be performed, for example, by applying the inverse function used for preprocessing and displaying the output value as a revenue currency value. It is envisaged that postprocessing could include a linear function, a non-linear function, or another neural network.

The output value produced by the neural network represents the predicted value, and by calculating the actual value from data retrieved from the memory, the correctness of the predicted value can be determined as the fit of the predicted data to the actual data. For example, where the neural network is trained to predict the revenue of machine bank 30 from Figure 3, the value output by the neural network could be compared to the actual revenue generated by machine bank 30.

The weights of the network can then be adjusted, based on the comparison between the predicted data and the actual data. These weights may be adjusted by any known algorithm suitable for the purpose, for example, a back propagation algorithm.

As indicated at 82, if the predicted data is not a good fit to the actual data, the learning algorithm may be repeated until such time as a good fit is obtained.

Figure 6 illustrates the typical results of neural network training based on the data from Figure 3. The objective in this learning process is to train the network to predict the revenue of machine bank 30. The actual revenue of machine bank 30 is shown in red and the predicted revenue of machine bank 30 is shown in green. The y-axis represents the proportion of actual revenue to the maximum revenue, in the range 0% to 100%. The x-axis represents time in hours.

Once learning is complete, the neural network may then be used to predict the revenue generated by machine bank 30 in a subsequent two week period. Figure 7 illustrates use of the preferred system to predict revenue. The neural network is first activated as shown at 90. The network calculates and outputs predicted data representing future interactions between customers and merchants.

As indicated at 92, this data is retrieved from the neural network and as shown at 94, the data is displayed to the user, following which the neural network is deactivated as shown at 96.

Figure 8 shows the actual revenue generated by machine bank 30 in a subsequent two week period in red. The predicted revenue of machine bank 30 over the same period is shown in green.

It will be envisaged that the invention used in this way may predict and display data to a user representing future interactions between customers and merchants.

Figure 9 illustrates another source of data for the invention. In this example, the invention is applied to predicting the revenue generated by machine bank 100. Data is collected which represents revenue generated by machine 100 in addition to neighbouring machine banks, 102, 104, 106, 108, 110 and 112.

Revenue generated by each of the machine banks over a one month period has been stored. In the last two weeks of the one month period, machine bank 100 has been changed. For example, individual gaming machines within machine bank 100 could have been either removed or replaced or alternatively, the entire machine bank could be replaced with another machine bank, or machine bank 18 could be moved to a different position or orientation.

Figure 10 illustrates a preferred neural network 120 for processing the data from Figure 9. The network 120 has seven input nodes in input layer 122, ten nodes in hidden layer 124 and one node in output layer 126. It will be appreciated that the numbers of nodes in the layers could be varied to a number suitable for the particular application. Each input node is arranged to receive interaction data involving one of machine banks 102, 104, 106, 108, 110 and 112. Signals are weighted in the same manner as described above with reference to Figure 4.

The neural network 120 is trained on the interaction data for the first two weeks of the month period prior to the change in machine bank 100 in the manner described above with reference to Figure 5.

Figure 11 shows the typical results of neural network training based on the data from Figure 9. The actual revenue of machine bank 100 is shown in red, and the predicted revenue of machine bank 100 is shown in green.

After training, the invention may be used, for example, to predict the revenue generated by machine bank 100 in the last two weeks of the month period to estimate the resulting revenue if machine bank 100 had not been changed.

This predicted revenue could be compared with actual revenue obtained from memory 6 as shown in Figure 12. Actual turnover of machine bank 100 is shown in red, while predicted revenue for machine bank 100 is shown in green. The user may then form an opinion regarding the benefit of the change in machine bank 100 based on the difference between actual revenue and the revenue which would have been obtained had machine bank not been changed. From Figure 12, it is clear that in this case, revenue would be greater if machine bank 100 had not been changed.

On this basis, the merchant may wish to undo the change to machine bank 100 to increase revenue.

It is within the scope of the invention to include additional inputs to the neural network. For example, the network could include an input to receive date and/or time data. By training the network using date and/or time data, the network can then be used to predict future revenue given a particular date and/or time. Where a date

and/or time input is to be disregarded, the input can be assigned a null weight to ensure that a null signal is passed to further neurons within the network.

In summary, the invention provides an interaction prediction system and method designed to assist a casino or gaming machine operator to predict future revenue from individual gaming machines in a casino. It will be appreciated that the same invention could also have application in other areas, for example, the layout and arrangement of products in retail premises and the resulting sales of those products.

The foregoing describes the invention including preferred forms thereof. Alterations and modifications as will be obvious to those skilled in the art, are intended to be incorporated within the scope hereof.

RUSSELL McVEAGH ~~WEST WALKER~~

per
ATTORNEYS FOR THE APPLICANT

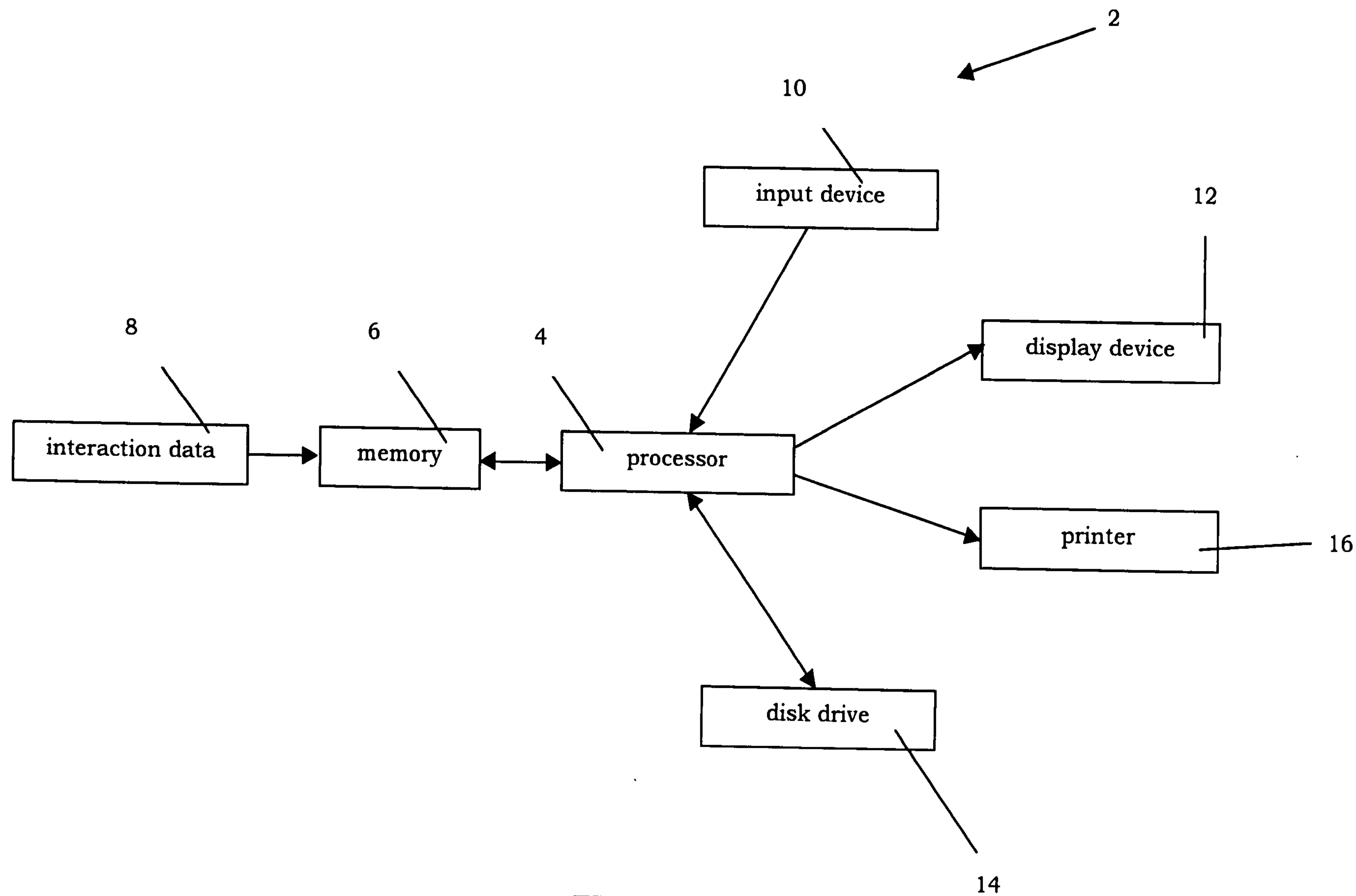

2
10
input device
12
display device
8
interaction data
6
memory
4
processor
printer
16
disk drive
14

FIGURE 1

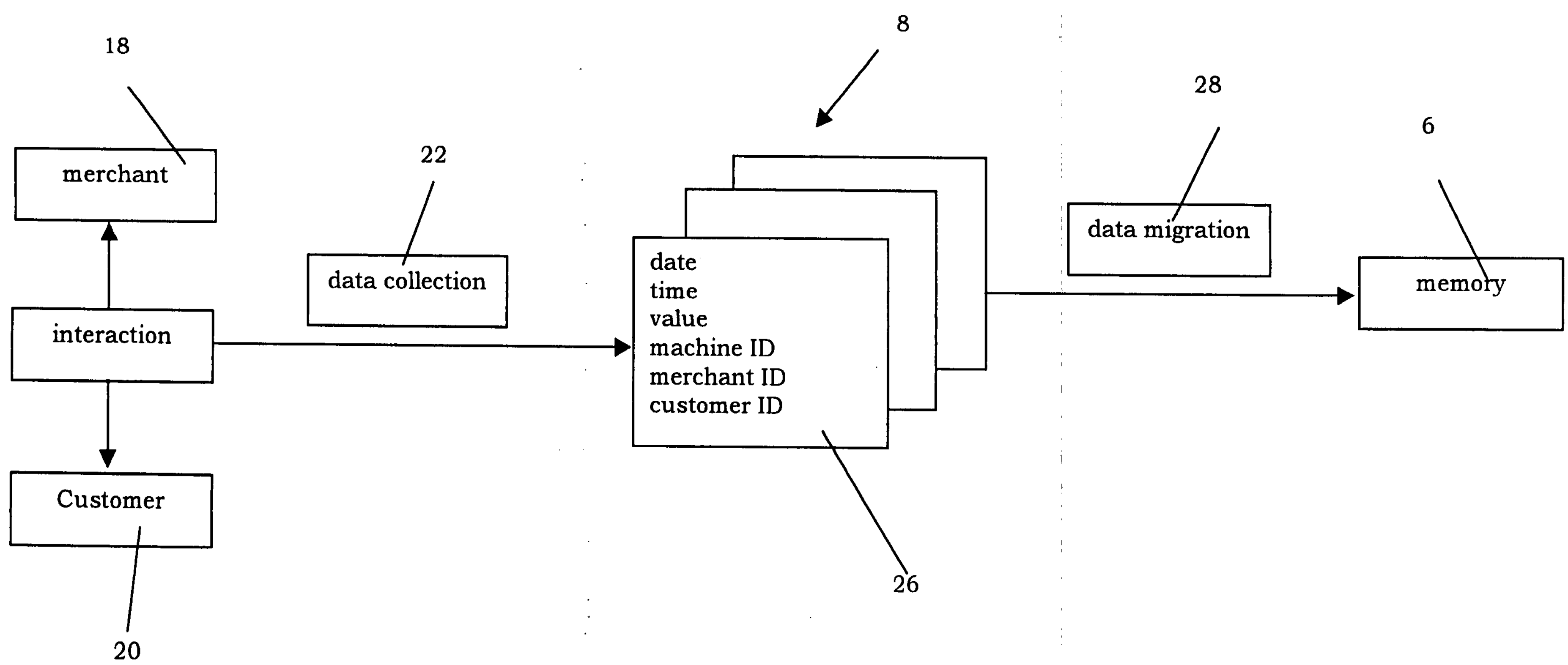

18
merchant
interaction
Customer
20
22
data collection
8
date
time
value
machine ID
merchant ID
customer ID
26
28
data migration
6
memory

FIGURE 2

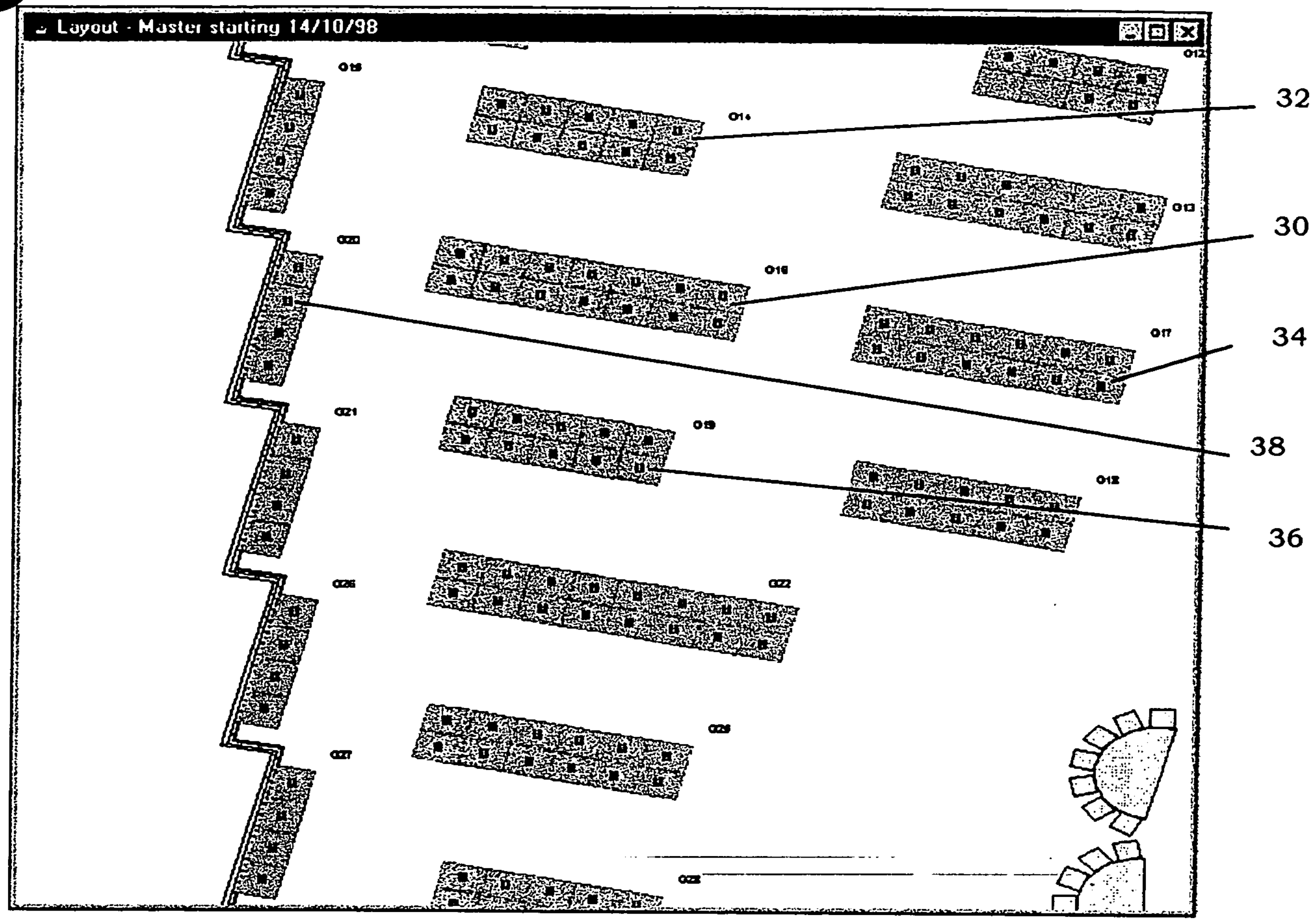


FIGURE 3

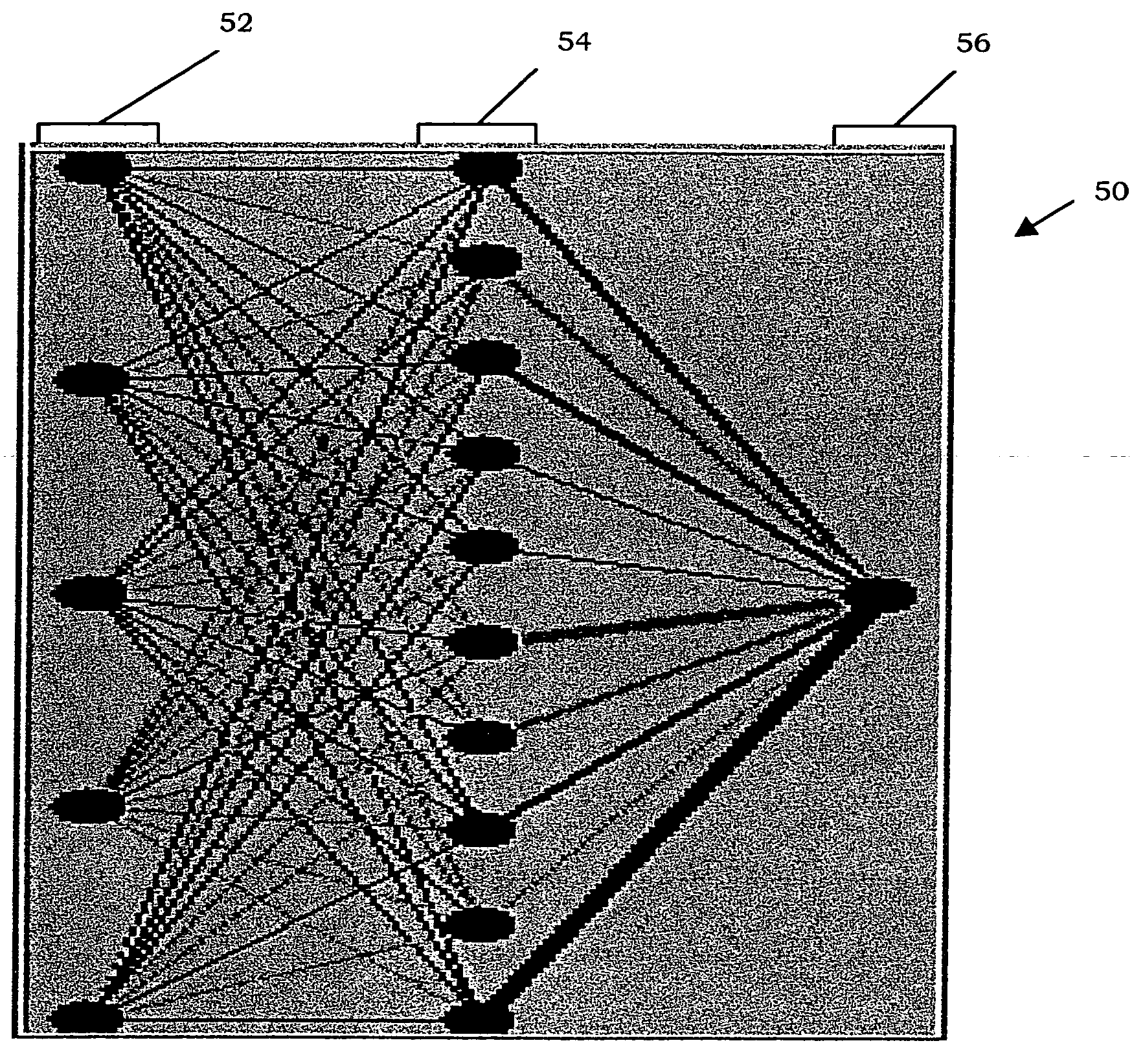


FIGURE 4

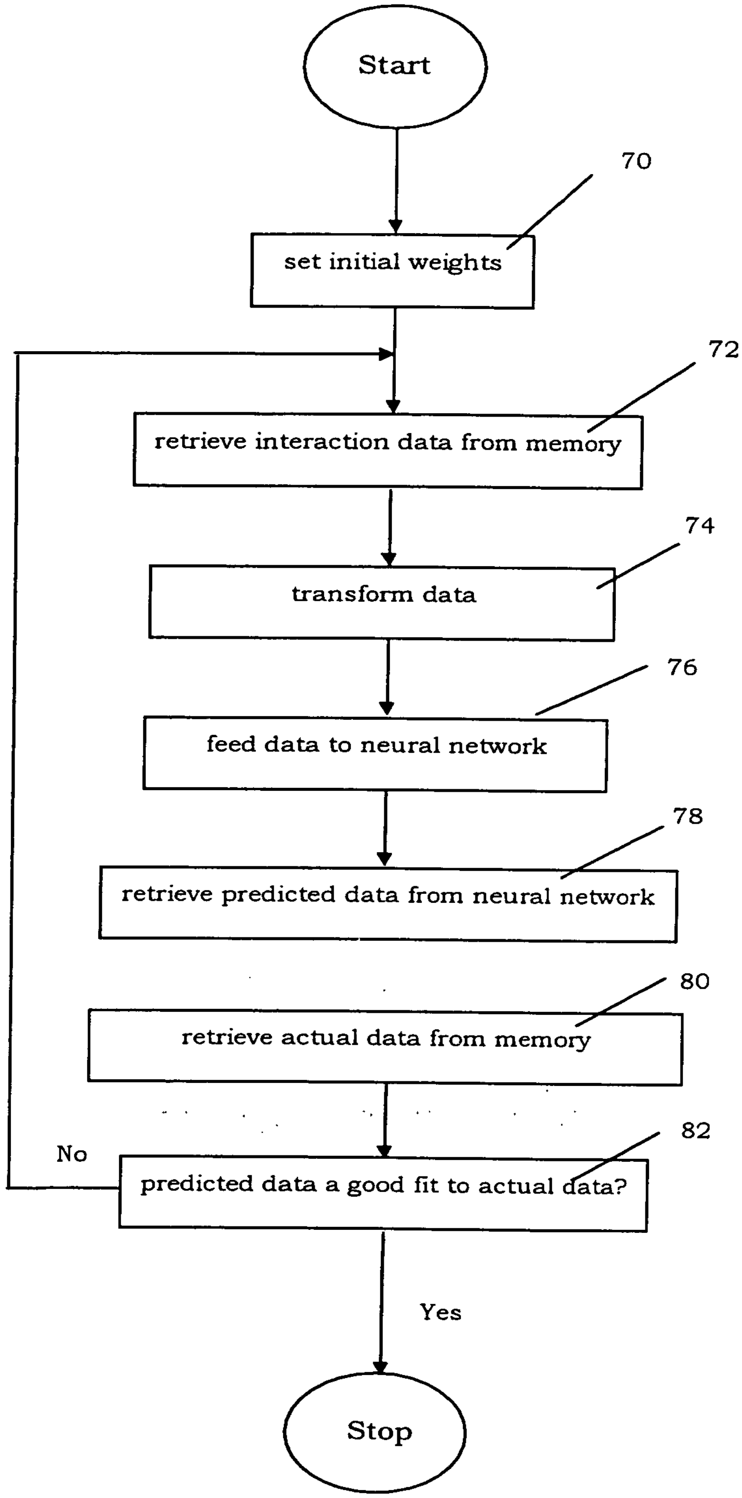

Start
70
set initial weights
72
retrieve interaction data from memory
74
transform data
76
feed data to neural network
78
retrieve predicted data from neural network
80
retrieve actual data from memory
82
No
predicted data a good fit to actual data?
Yes
Stop

FIGURE 5

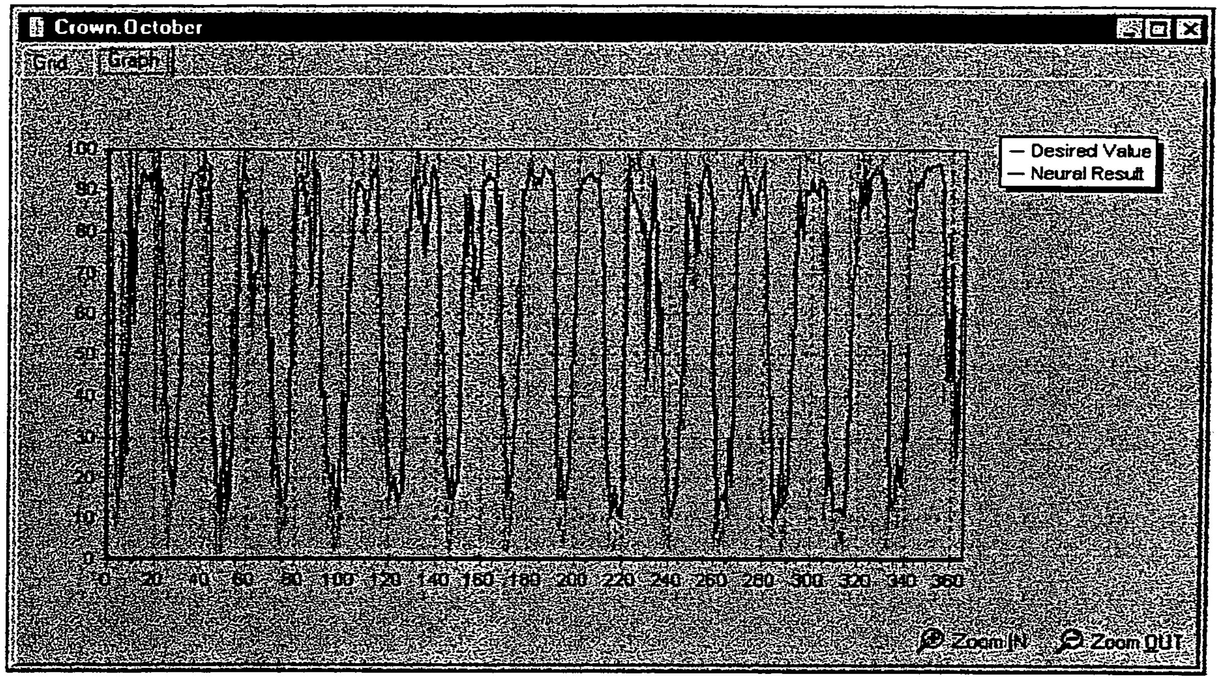

Crown.October
Grid
Graph
100
90
80
70
60
50
40
30
20
10
0
0 20 40 60 80 100 120 140 160 180 200 220 240 260 280 300 320 340 360
— Desired Value
— Neural Result
Zoom IN
Zoom OUT

FIGURE 6

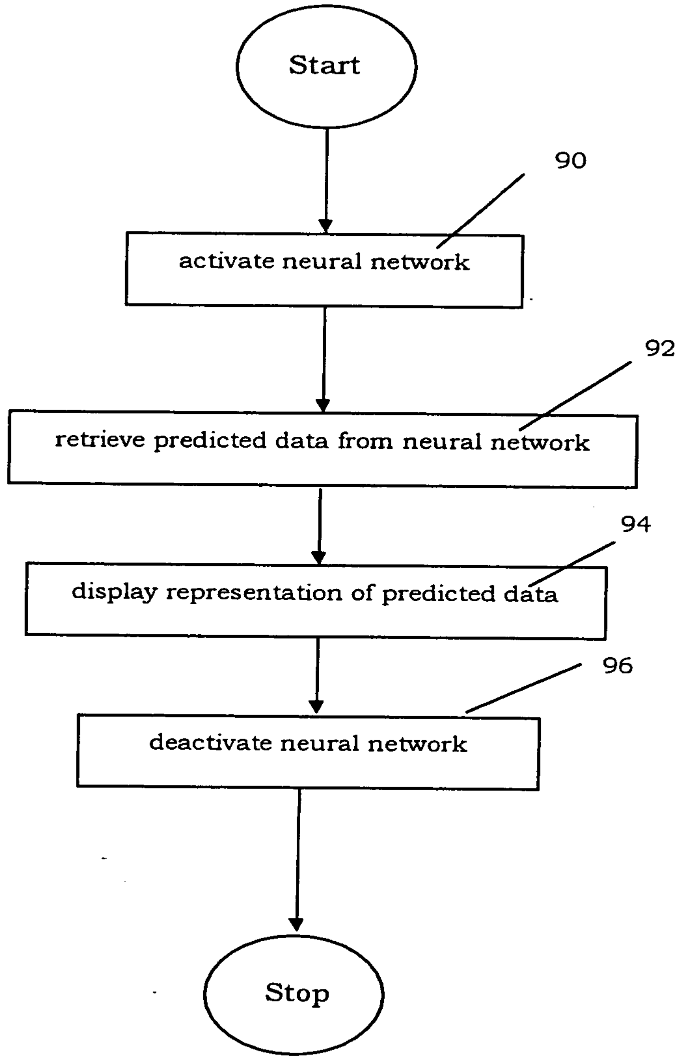
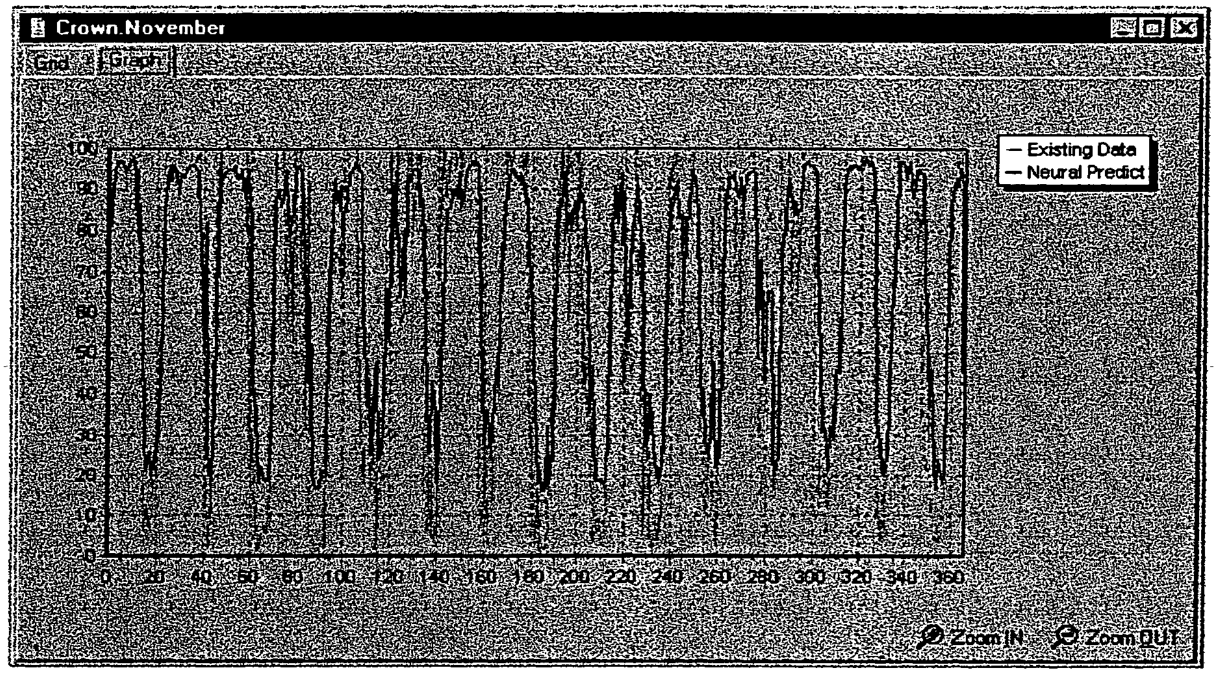

Start
90
activate neural network
92
retrieve predicted data from neural network
94
display representation of predicted data
96
deactivate neural network
Stop

Figure 7


Crown.November
Grid
Graph
100
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80
70
60
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40
30
20
10
0
0
20
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60
80
100
120
140
160
180
200
220
240
260
280
300
320
340
360
Existing Data
Neural Predict
Zoom IN
Zoom OUT

FIGURE 8

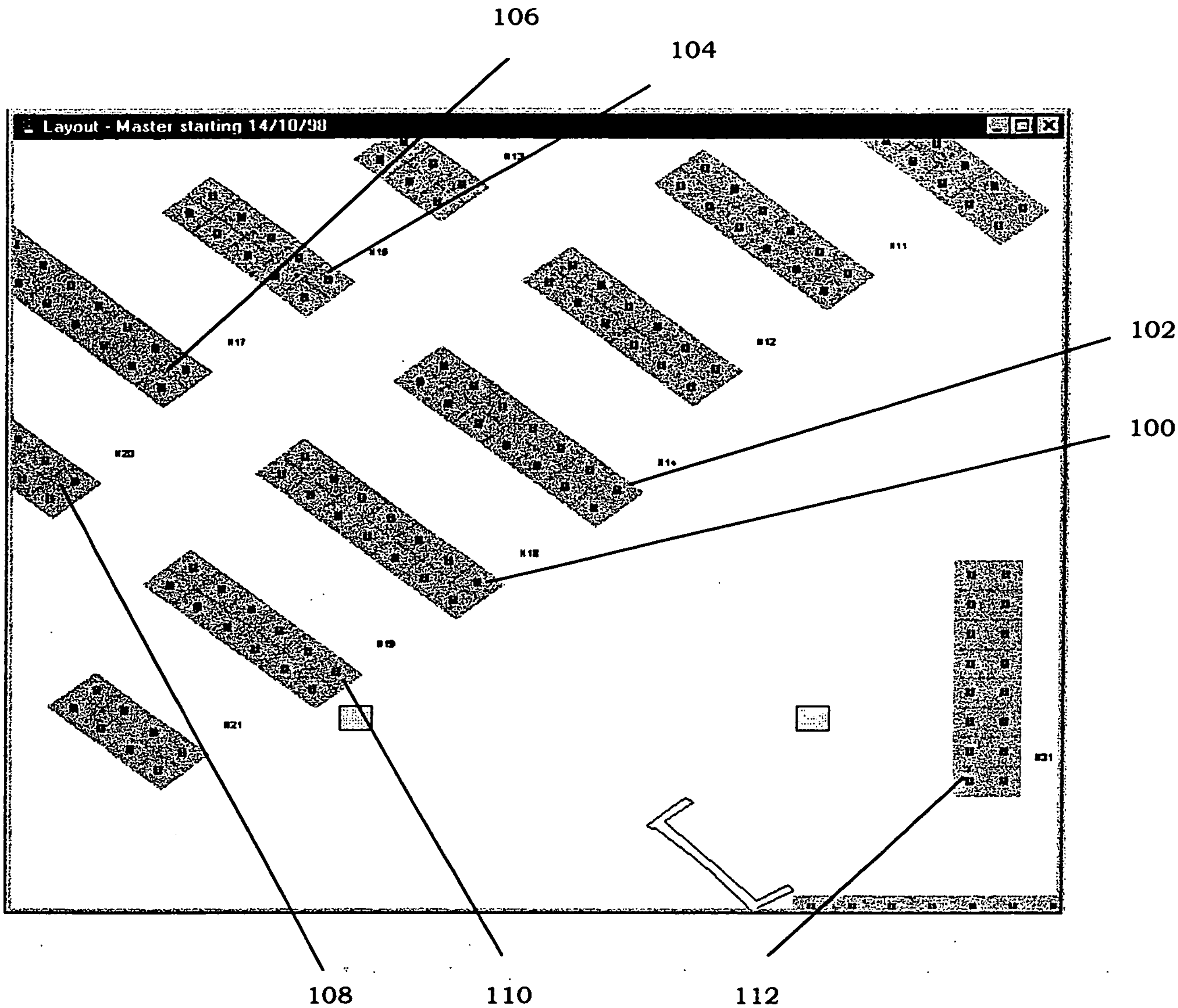


FIGURE 9

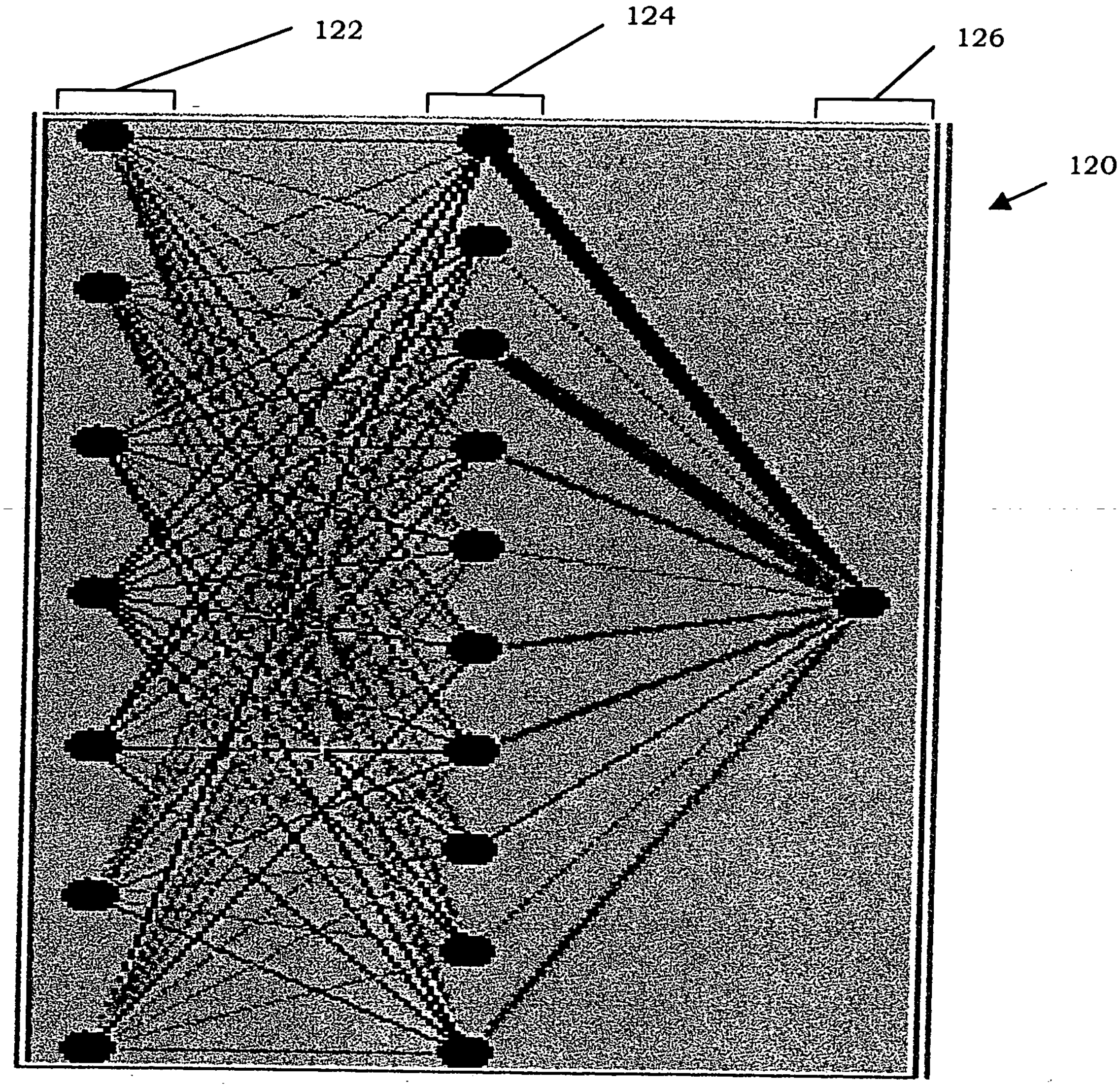
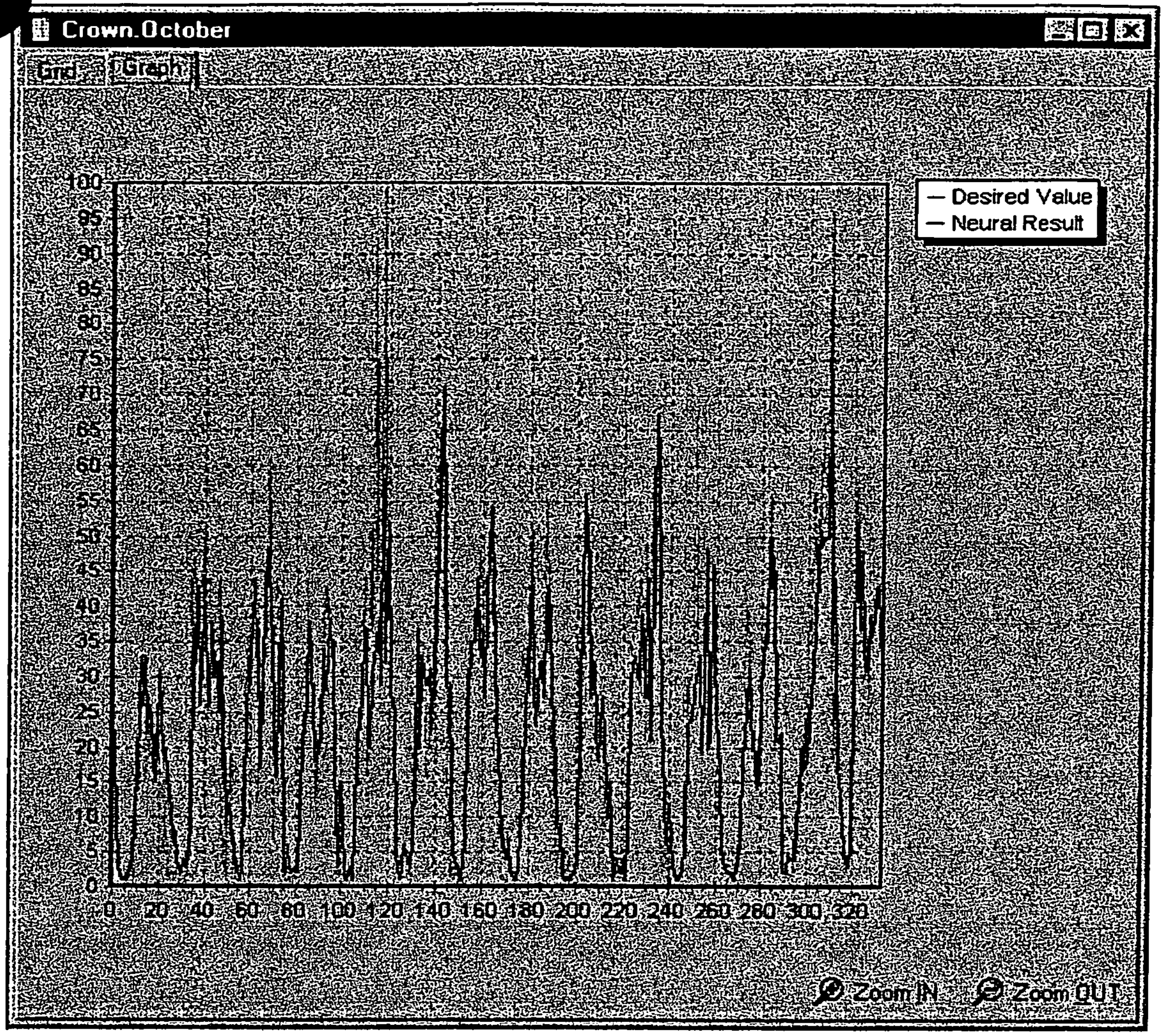


FIGURE 10



Crown.October
Grid
Graph
100
95
90
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75
70
65
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55
50
45
40
35
30
25
20
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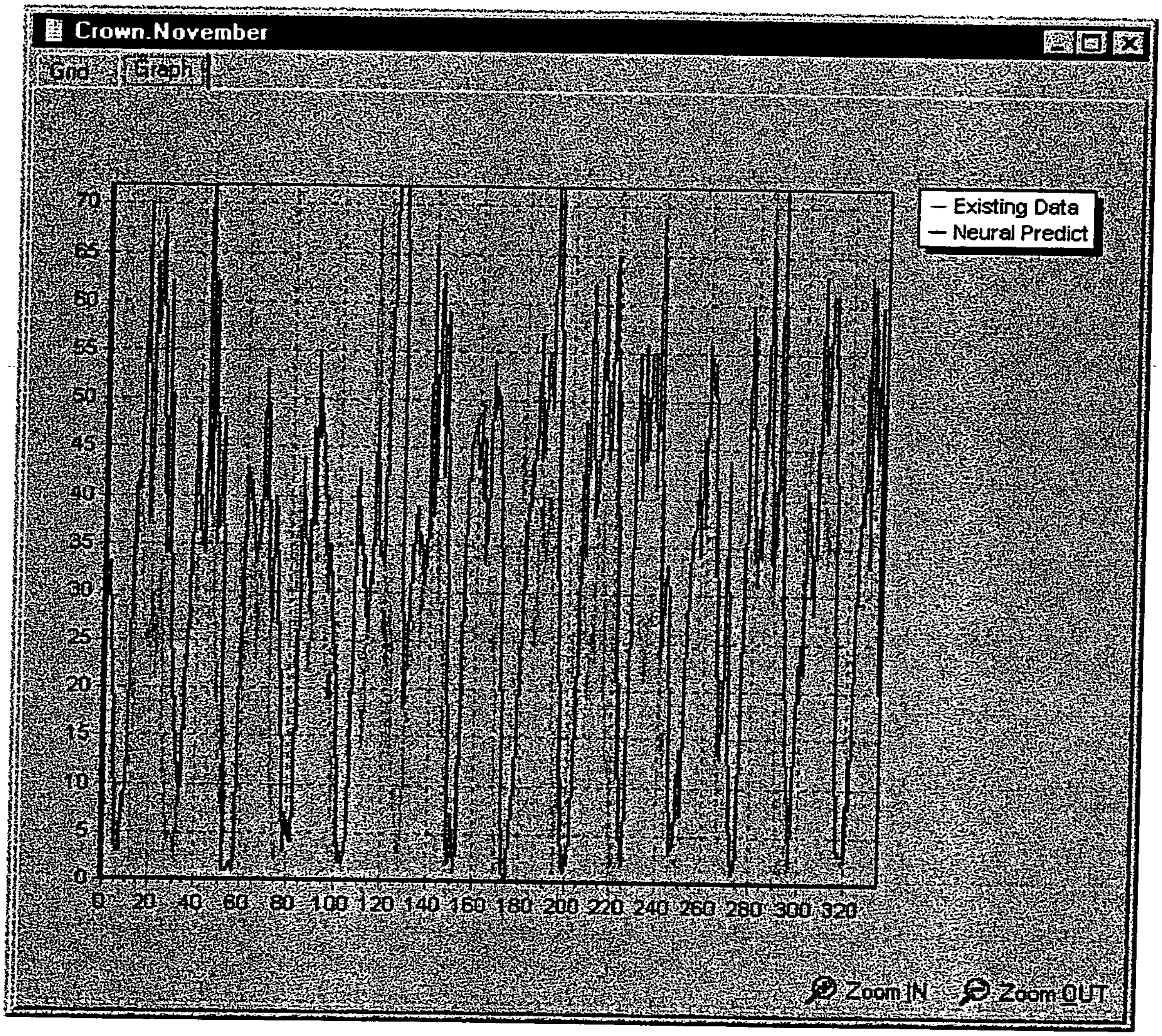
10
5
0
0 20 40 60 80 100 120 140 160 180 200 220 240 260 280 300 320
— Desired Value
— Neural Result
Zoom IN
Zoom OUT

FIGURE 11


Crown.November
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20
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60
80
100
120
140
160
180
200
220
240
260
280
300
320
Existing Data
Neural Predict
Zoom IN
Zoom OUT

FIGURE 12